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## Modeling US Households' Demand for Liquid Wealth in an Era of Financial Change

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# **Modeling U.S. Households' Demand for Liquid Wealth in an Era of Financial Change**

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## **Abstract**

Money demand models overpredicted M2 growth in the United States from 1990 to 1993. We examine this overprediction using a model of household demand for liquid wealth. The model is a dynamic generalization of the almost-ideal demand model of Deaton and Muellbauer (1980). We find that the own-price elasticity of money demand rose substantially after 1990. We also find important cross-price elasticities of money with respect to other liquid financial assets, notably with respect to mutual funds. Incorporating these and other features helps explain nearly 50 percent of the shortfall in M2 growth over the period in question. It also suggests that households respond more rapidly to changes in market interest rates than is assumed in some limited-participation general equilibrium macroeconomic models.

**Keywords:** money demand, ideal demand model, missing money

**JEL Classification:** E41, EC32

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## 1. Introduction

This paper presents a new dynamic model of the portfolio behavior of U.S. households. The model, a variant of Deaton and Muellbauer's (1980a) Almost Ideal Demand System, permits us to impose (and test) long-run restrictions while still allowing a flexible pattern of short-run adjustment. We construct and estimate the model on a new, fairly complete set of household liquid assets from 1984-1993. Of particular importance is the inclusion of carefully specified data on bond and equity mutual funds, a popular investment among household during the 1990s.

The portfolio behavior of households is an increasingly important topic in monetary economics, and our model contributes to two related areas. First, "limited participation" models of the monetary transmission mechanism assume that households adjust their assets and liabilities only weakly in response to changes in market interest rates; see Fuerst (1992), Christiano and Eichenbaum (1992), and references therein. The sluggish response of households in these models allows monetary policy shocks to generate liquidity effects and affect real economic activity. Our results suggest that households may respond more rapidly to market shocks than has previously been assumed, with own-price elasticities for liquid assets greater than unity.

Second, our results suggest an explanation for some of the weakness of M2 growth during the 1990s. The years 1990 to 1993 have been labeled by some as the most recent "case of missing money". Over this period, the Federal Reserve Board's model of M2 demand, for example, significantly overpredicted the growth of M2, as shown in Figure 1. While a number of authors have sought to explain the weakness with respecified aggregate money demand models, none have explicitly modeled the balance sheet behavior of households even though households hold about 90 percent of M2. At about the same time, household acquisition of debt also slowed, while inflows into mutual funds jumped (Figure 2). These adjustments likely reflect, at least in part, a rethinking on the part of households of their traditional relationships with banks. Perhaps equally important, however, this may reflect a strong response of households to changes in market yields that may be contrary to the assumptions of limited participation models.

## 2. Theoretical Framework

Deaton and Muellbauer's (1980a) AIDS framework assumes a representative consumer who maximizes utility period-by-period, subject to his budget. Barr and Cuthbertson (1990), drawing on the work of Weale (1986), restate the AIDS model slightly to incorporate financial assets. In

their setup, consumers choose an array of real assets (and possibly liabilities)  $a_i$  so as to maximize expected one-period ahead utility. The consumer's preferences are represented by the AIDS expenditure function:

$$\ln W(u, p) = \alpha_0 + \sum_i \alpha_i \ln p_i + 1/2 \sum_i \sum_j \gamma_{ij}^* \ln p_i \ln p_j + u \beta_0 \prod_i p_i^{\beta_i} + \phi^* \ln Y^r \quad (1)$$

where  $\alpha_i$ ,  $\beta_i$ ,  $\gamma_{ij}^*$ , and  $\phi^*$  are parameters,  $W$  is expenditure on liquid wealth in period  $t$ ,  $w$  is its real (deflated) counterpart,  $p_j$  is the expected real price of asset  $j$  conditional on information available at the beginning of period  $t$ ,  $Y^r$  is expected real income (or consumption) during period  $t$ . As Weale notes, the term  $\phi^* \ln Y^r$  can be interpreted as representing a demand for transactions balances. The consumer's expenditure function can thus be seen as admitting both a transactions demand for liquid wealth, as well as a savings or portfolio motive. As a referee has pointed out to us, an alternative justification for including the income or consumption variable  $Y^r$  is the "AIDS with rationing" model proposed by Offenbacher (1982).

Using Shephard's lemma and straightforward algebra gives the proposed budget shares (asset demands)  $s_i = p_i q_i / W(u, p)$ :

$$s_i = \alpha_i + \sum_j \gamma_{ij} \ln p_j + \beta_i \ln(w/P^*) + \phi_i \ln Y^r \quad (2)$$

where  $\gamma_{ij} = 1/2(\gamma_{ij}^* + \gamma_{ji}^*)$ ,  $\phi_i = \beta_i \phi^*$ , and  $P^*$  is an aggregate price level given by:

$$\ln P^* = \alpha_0 + \sum_i \alpha_i \ln p_i + (1/2) \sum_i \sum_j \gamma_{ij} \ln p_i \ln p_j \quad (3)$$

The share of a household's budget allocated to good  $i$  thus depends on the prices of all goods, the ratio of expenditure on liquid assets to the overall price index, and real income or consumption.

Following Barnett (1980), we measure prices as  $(R^b - r_i)/(1 + R^b)$ , where  $r_i$  is the return on the  $i$ th asset and  $R^b$  is the return on a benchmark asset. The overall price index  $\ln P^*$  is then approximated by the Stone price index  $\ln P^* = \sum_i \bar{s}_i \ln p_i$ , where  $\bar{s}_i$  is the sample average for  $s_i$ .

Because the budget shares must sum to one, we have the "adding-up" restrictions:

$$\sum_i \alpha_i = 1; \quad \sum_i \gamma_i = 0; \quad \sum_i \beta_i = 0$$

The axioms of rational consumer choice provide additional restrictions. Homogeneity of degree zero in prices requires that  $\sum_j \gamma_{ij} = 0$ , while symmetry of the Slutsky matrix requires that  $\gamma_{ij} = \gamma_{ji}$ . Table 1 presents formulas for Hicksian (income-compensated), Marshallian, and income elasticities.

Table 1: Elasticity Formulas for AIDS Model

	Own-Price	Cross-Price
Hicksian	$h_{ii} = [\gamma_{ii} + s_i^2 + \beta_i^2 \ln(w/P^*)]/s_i - 1$	$h_{ij} = [\gamma_{ij} + s_i s_j + \beta_i \beta_j \ln(w/P^*)]/s_i$
Marshallian	$\eta_{ii} = [\gamma_{ii} - \beta_i(\alpha_i + \sum_k \gamma_{ik} \ln p_k)]/s_i - 1$	$\eta_{ij} = [\gamma_{ij} - \beta_i(\alpha_j + \sum_k \gamma_{jk} \ln p_k)]/s_i$
Income	$\xi_i = (\beta_i/s_i) + 1$	

## 2.1 Implicit Separability and N-stage Budgeting

We impose further structure on the AIDS cost function by assuming that it is implicitly and recursively separable. Households are assumed to make their decisions about liquid financial wealth in three stages. In the first stage, consumers choose their holdings of liquid assets and liabilities. In the second stage, consumers allocate liquid assets among broad categories, one of which is money. In the third stage, consumers allocate money holdings into checkable deposits, savings and time deposits, and money market funds. This kind of separability is convenient because it greatly reduces the number of prices (and therefore the number of parameters) we must consider at each stage of the budgeting process.

In particular, we assume the cost function can be written as:

$$E(u, e_1(u, \vec{p}_1), e_2(u, \vec{p}_2, e_3(u, \vec{p}_3)))$$

where  $e_1$  represents “expenditure” on liquid liabilities,  $e_2$  represents expenditure on liquid assets,  $e_3$  represents expenditure on various kinds of money, and  $\vec{p}_j$  represents the vector of prices appropriate for that set of assets. Serletis (1991) has advocated a similar approach to modelling demands for monetary aggregates. However, he works with the indirect utility function, rather than the cost function.

Deaton and Muellbauer (1980b) show that with this kind of separability a variant of Shephard’s lemma holds at each stage of the budgeting process, allowing one to model “within-group” wealth shares using only the prices of goods in that group and wealth spent on that group. They also show that the subcost functions  $e_j(u, \vec{p}_j)$  can be used as group price indices. Following this logic, we first estimate budget share equations for components of money and then use those estimates to form a subcost function that is a price (index) for money. This price (index) is used in the middle stage, where we estimate share equations for money and other liquid assets. From these latter estimates we form a subcost function for liquid assets that we use as a price (index) in estimating the share equations in the final stage (liquid assets and liquid liabilities).

### 3. Adjustment to Long-Run Equilibrium, Cointegration, and Other Econometric Concerns

Because households likely adjust their asset holdings with some lag, we allow for dynamics. It is also important to incorporate dynamics for purely econometric reasons. Anderson and Blundell (1982) noted that: “the literature on systems of demand equations abounds with examples of empirical studies in which restrictions from economic theory, such as homogeneity and symmetry, are rejected”. They demonstrate that such rejections may result from improper treatment of dynamics, and therefore advocate the use of error correction models. Several papers have subsequently estimated AIDS or translog models in an error-correction framework [Barr and Cuthbertson (1990), Serletis (1991), Anderson (1991)].

More recently, Ng (1995) has shown that such rejections may stem from the nonstationarity of prices and shares. She shows that when prices and shares in AIDS models are nonstationary, ignoring the nonstationarity tends to lead to too frequent rejection of homogeneity. The antidote is to model prices and shares as a cointegrated vector. The specific estimation approach she relies on is dynamic OLS (Stock and Watson, 1993). We take a slightly different approach, relying on the suggestions of Phillips and Loretan (1991) that the cointegrated vector be estimated in non-linear error correction form.

Stacking the  $j$  equations in (4), we can write them as:

$$s^* = \beta X \quad (4)$$

where  $s^*$  is a  $J$ -length vector of desired long-run shares,  $X$  is an  $1 \times (J+3)$  matrix of the right-hand variables, and  $\beta$  is an  $(J+3) \times J$  matrix of parameters. If  $s^*$  and  $X$  are indeed cointegrated, then, as Phillips and Loretan show, proper inferences about  $\beta$  can be drawn by estimating the nonlinear error-correction model:

$$\Delta s_{i,t} = \Gamma(s_{i,t-1} - \beta X_{t-1}) + A(L)\Delta X_t + B(L^{-1})\Delta X_t \quad (5)$$

where  $\Gamma$  is a  $(J \times J)$  matrix of adjustment parameters, and where  $A(L)$  and  $B(L^{-1})$  are polynomials in lags and leads of  $\Delta X_t$ .

As Ng (1995) points out, there is no set rule for choosing the order of the polynomials  $A(L)$  and  $B(L^{-1})$ . She also notes that in share models even low order polynomials can quickly deplete degrees of freedom. Consequently, we follow her approach and limit ourselves to just one lead and

one lag. Like Ng, we tried adding up to four leads and lags and we find, as she did, that parameters were similar to those estimated with one lead and one lag, but that standard errors were larger.

According to (5), consumers do not instantaneously adjust their portfolios to their long-run equilibrium in response to shocks. The speed of their adjustment is given by  $\Gamma$ . Since  $\Gamma$  is a matrix, the adjustment of any particular share toward its equilibrium may depend on shocks to all of the other wealth shares. In particular, money demand may respond with a lag to shocks to capital-uncertain assets such as stocks and bonds, as well as to financial liabilities.

Econometrics issues raised by equation (5) are threefold. First, as Phillips and Loretan note, the model must be estimated by non-linear methods. Second, although (5) is a system of  $J$  equations, only  $(J - 1)$  of the equations are independent because the shares  $s_i$  sum to one. This gives rise to the well known problem that share models, such as AIDS or translog, have singular covariance matrices. The singularity is avoided by dropping one of the  $J$  equations from the estimation procedure. Parameter estimates and standard errors for the omitted equation can always be derived from those of the first  $(J - 1)$  equations. In TSP this is easily accomplished using “FRML”s and the “ANALYZ” command. Third, because (5) is indeed a system, systems methods must be used to test or impose symmetry and homogeneity restrictions. In view of these issues, we estimate (5) using the non-linear least squares routine in TSP.

#### 4. Data

Our AIDS model is based on monthly data from January 1984 to July 1993. Since we are interested in assets (and liabilities) that may substitute for what is traditionally known as money we considered only liquid assets and liquid liabilities, and only those that we believe are tightly linked to household spending.

Following the logic in section 2.1, we have grouped these liquid assets and liabilities into three blocks. The first is a two-equation money block, with the first equation measuring the demand for other checkable deposits (OCDs) plus savings deposits, and the second representing demand for small CDs plus retail money market funds (MMMFs).

The money block is notable for what we exclude. First, we exclude overnight RPs and overnight Eurodollars. Acknowledging that overnight RPs and Eurodollars are volatile and are unlikely to represent retail balances, the Federal Reserve recently redefined M2, choosing to move these components into M3.

More conspicuously, we also exclude currency and demand deposits from our analysis. We do this primarily for practical reasons. In earlier versions of this paper, we tried various ways of estimating AIDS models that included demand deposits and currency but were quite unsuccessful in that the coefficients in the “money” block were typically insignificant and/or of the wrong sign. On the advice of a referee, we also tried estimating block 1 with a share equation for M1-type balances (currency+demand deposits+OCDs) and a second share equation for non-M1 balances in M2 (savings+small time deposits+money market funds). This approach was similarly unsuccessful. Moreover, contrary to the results in our preferred approach of excluding currency and demand deposits, including currency and demand deposits leads to rejection of homogeneity and symmetry restrictions in the first two blocks.

In part, our lack of success on this front may reflect the fact that currency and demand deposits likely have large components that are unrelated to households’ consumption patterns. Lately, currency has been tainted by the realization that a substantial portion of U.S. currency is probably held outside the United States. Demand deposits are more difficult to dismiss, as a referee has pointed out to us. Still, indirect evidence suggests that demand deposits are closely linked to the securities transactions of financial institutions. The velocity of demand deposits, as measured by turnover ratio statistics collected by the Federal Reserve, is far too high to represent retail influences. For example, the turnover ratio for demand deposits in the United States is about 900 per year and is about 4000 per year for New York City. If this represented household activity, it would suggest that the average household receives a paycheck roughly 75 times ( $900/12$ ) per month. The fact that the turnover ratio for New York City is so high is suggestive, as the city attracts a high proportion of the nation’s securities transactions. In contrast, the turnover ratio for the other checkable component of M1, OCDs, is 15 times per year, about what we would expect if households receive paychecks once or twice a month. In addition, demand deposit growth has been poorly tracked by money demand models (Mahoney, 1988) since 1985. Mahoney suggests that this may owe to compensating balances, mortgage activity, and new financial instruments. Duca (1990) finds some evidence that the erratic behavior of demand deposits stems in part from unscheduled repayments of mortgages underlying mortgage-backed securities. Such influences on demand deposits are largely unrelated to household spending patterns.

The second block consists of four liquid asset equations: money (OCDs, savings, small CDs,



MMMFs), long-term mutual funds, retail holdings of U.S. government Treasury securities (non-competitive tenders), and savings bonds.

The last block has two equations; one each for liquid assets (money, mutual funds, noncompetitive tenders, savings bonds) and liquid liabilities, taken to be consumer credit.

The data for these blocks are drawn from a number of sources. Data on monetary assets and savings bonds are taken from the Federal Reserve's H.6 publication. All of these data are seasonally adjusted. Data on total assets of long-term mutual funds are available from Investment Company Institute. Data on noncompetitive tenders are taken from the Treasury Bulletin, and are measured on a net basis. Net noncompetitive tenders are measured as the difference between the gross noncompetitive tenders figures listed in the Treasury Bulletin and the gross noncompetitive tenders of the same maturity lagged by that same maturity. We work with net noncompetitive tenders because they are thought to represent retail demand. Because net noncompetitive tenders can be viewed as a flow, we translate this series into a stock by adding their cumulative sum to a base level of Treasury securities held by the household sector in December 1983, as reported by the Federal Reserve in its flow of funds accounts. Monthly data on consumer credit are available from the Federal Reserve.

Our monetary series and raw mutual fund data are inconsistent in several respects: (1) long-term mutual fund assets are not seasonally adjusted; (2) the monetary data exclude assets held in IRA/Keogh accounts, while the raw long-term mutual fund data include them; (3) M2 assets exclude money market funds that cater to institutions (which are included at the M3 level), but mutual fund assets include them; (4) mutual fund assets are reported as of the last day of each month, whereas monetary data are month averages. Attempting to rectify these inconsistencies, we made several adjustments to raw mutual fund assets. We tried to seasonally adjust the mutual fund assets but Census X-11 indicated no apparent seasonality. We subtracted from the raw mutual fund assets IRA/Keogh assets in long-term mutual funds and also an estimate of institutional holdings of long-term funds. Last, we created approximate month-averages of the new long-term mutual fund assets (less IRA/Keoghs and institutional assets) by taking a 2-month moving average of adjacent month-end observations.

Rates of return used to create the prices  $p_j$  are taken from a number of sources. Nominal rates of return on OCDs, savings plus MMDAs and small time deposits are taken from the Federal Reserve's

FR2042 Monthly Survey of Selected Deposits. The rate of return on M2 type money market funds is taken to be the 30 day yield reported by IBC/Donoghue for all taxable money market funds. These rates are put on an effective basis.

Return variables for long-term mutual funds are more troublesome. Theoretically, price variables should be constructed from nominal rates of return expected on assets between periods  $t$  and  $t + 1$ . For bank deposits and money market funds the distinction between expected and actual rates of return likely makes little difference; M2-type assets are not subject to revaluations and their yields are highly serially correlated. Revaluations are, however, a prominent feature of long-term mutual funds and, as a result, expected one-period ahead returns may deviate significantly from current period returns. We experimented with several return variables for long-term mutual funds. Two measures that proved ineffective, in a strictly econometric sense, were a yield curve variable—the difference between yields on 30 year Treasury bonds and 3 month Treasury bills—and the ex-post total return on mutual funds. The most satisfying measure, which can be viewed as a “long-run” average return on capital uncertain assets, is constructed from one-month returns on the NYSE 5000 and a Merrill Lynch bond index:

$$r_{fund} = [w_{t-1}(NYSE_t/NYSE_{t-1} - 1)^{(1/t)} + (1 - w_{t-1})(Index_t/Index_{t-1} - 1)^{(1/t)}]$$

where  $w_{t-1}$  is the percentage of mutual fund assets held in stock mutual funds (last month),  $NYSE$  is the NYSE 5000 stock price index and  $Index$  is a Merrill Lynch index of bond returns. Although we lack theoretical justification for this measure, it has some intuitive appeal. It is, in essence, a long-run geometric mean of returns on stocks and bonds. Consumers may be unable to predict near-term returns on stocks and bonds with much certainty, focusing instead on the longer-run, where such returns might be better predicted. Barr and Cuthbertson (1990) found that similar variables—long moving averages of ex-post annual returns on capital uncertain assets—sufficed in modelling the household sector of U.K. flow-of-funds accounts.

The return on noncompetitive tenders is taken to be a simple average of the yield on three month Treasury bills and 10-year Treasury bonds. The return on savings bonds is the current effective rate set by the Treasury Department. This rate is reset semi-annually (in May and November), and fluctuates with market interest rates. The return on consumer credit is taken to be the negative of the simple average of rates paid on consumer credit cards and on new auto loans. As a benchmark rate,  $R^b$ , we use the yield on the 30-year Treasury bond.

Our data set is rounded out by a few real side variables. We use real disposable personal income as our measure of  $Y$  and the implicit deflator on disposable personal income as a price deflator.

## 6. Empirical Results

The stepping-off point of our empirics is testing for stationarity of the variables in our model. Table 2 presents augmented Dickey-Fuller statistics for testing the null hypothesis of nonstationarity for the variables in each of our three blocks of equations. The null hypothesis is that the variable in question is nonstationary. The table reports t-statistics on  $\rho$  in the regression  $\Delta z_t = \alpha + \rho z_{t-1} + C(L)\Delta z_{t-1} + \beta t$ . The ADF tests for  $s_1$  and  $s_2$  in the first block exclude the constant and trend, as both appeared insignificant in preliminary regressions.

A large (negative) t-statistic suggests that the variable  $z_t$  is stationary. P-values are computed in TSP, which uses the response surface estimates reported in Table 1 of MacKinnon (1994). Following the suggestion of a referee, the lag lengths in  $C(L)$  were chosen using the data-based algorithm of Ng and Perron (1994). Their algorithm is a general-to-specific means of choosing an appropriate lag length for  $C(L)$ . They show that their algorithm greatly improves the power of the Dickey-Fuller test. We chose a maximum order (lag-length) for  $C(L)$  of 6.

With one exception, the statistics uniformly accept the hypothesis that all of the variables in all three blocks are nonstationary in levels, but stationary in first differences. The exception is that the variable  $s_2$  (long-term mutual funds) appears to be only marginally stationary in first differences (p-value of .19). We note, however, that when we follow the Ng and Perron routine, but introduce a trend-squared as well as a trend variable, and recompute the ADF test, the variable  $s_2$  is stationary in first differences (p-value of .01).

**Table 2 : ADF Tests for Stationarity of Variables**

Block 1: Money					
ADF-statistics	$s_1$	$s_2$	$\ln p_1$	$\ln p_2$	$w$
Level-Stationary ?	-1.57	-1.57	-2.33	-2.22	-1.73
(p-value)	0.85	0.85	0.47	0.53	0.79
Difference-Stationary?	-2.46	-2.46	-7.31	-7.08	-7.39
(p-value)	0.01	0.01	0.00	0.00	0.00

Block 2: Liquid Assets									
ADF-statistics	$s_1$	$s_2$	$s_3$	$s_4$	$\ln p_1$	$\ln p_2$	$\ln p_3$	$\ln p_4^r$	$w$
Level-Stationary ?	-.18	-1.78	-1.48	-1.57	-2.36	-2.37	-1.83	-1.54	-2.19
(p-value)	0.99	0.77	0.87	0.84	0.44	0.43	0.74	0.86	0.55
Difference-Stationary?	-5.59	-2.79	-7.03	-5.93	-6.85	-7.02	-6.71	-7.75	-6.65
(p-value)	0.00	0.19	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Block 3: Liquid Wealth						
ADF-statistics	$s_1$	$s_2$	$\ln p_1$	$\ln p_2$	$w$	
Level-Stationary ?	-2.41	-2.41	-2.37	-2.93	-2.01	
(p-value)	0.41	0.41	0.43	0.16	0.65	
Difference-Stationary?	-5.59	-5.59	-5.97	-9.07	-10.58	
(p-value)	0.00	0.00	0.00	0.00	0.00	

On the advice of a referee, we also computed unit-root tests which have stationarity as the null hypothesis because ADF tests are known to have low power of rejecting the null of nonstationarity in favor of stationary alternatives. The specific test we used is the KPSS test due to Kwiatkowski et al. (1992). For brevity's sake, we summarize the results (again, full details are available on request). The tests, like ADF tests, require us to choose a specific lag length for computing autocorrelations. We used lag-lengths of 4 and 12 and computed the KPSS statistics with trends included. The tests uniformly indicate that all of the variables are nonstationary in levels. However, the KPSS tests were less consistent than the ADF tests in finding our variables stationary in first differences. Instead, the KPSS tests tended to indicate that price and wealth variables were stationary in first differences, but that shares might be stationary only in second differences.

At first glance, this would appear to cast doubt on the results of the Dickey-Fuller tests in Table 2. However, the Monte Carlo evidence presented in Kwiatkowski et al. (1992) suggests that the KPSS test is, itself, subject to considerable size and power distortions. Moreover, with the ADF tests the lag-length has been chosen in some sense optimally by the Ng and Perron algorithm, whereas with the KPSS tests we arbitrarily restricted the lag-length to 4 or 12. For these reasons we suspect that in our case the KPSS tests are less reliable than the ADF tests. We also note that problems with the ADF test arise from its power, not its size (Schwert, 1989). This means that we can be fairly confident that the Dickey-Fuller tests are correctly concluding that our variables are stationary in first differences. What we must be less confident about is the ability of the ADF test to tell us whether our variables are stationary in levels. Fortunately, on this score, the tests agree:

they indicate that our variables are nonstationary in levels. We therefore tend to favor the results of the ADF and proceed all our variables are stationary after differencing once.

### 6.1 Model Estimates

Model estimates are shown in Table 3 for each of the three blocks of equations. Symmetry and homogeneity have been imposed in the first two blocks because hypothesis tests indicate they are accepted. For example, the Wald statistic for testing symmetry and homogeneity is, for the first block, asymptotically  $\chi^2(1) = .06$ , with a p-value of .79; for the second block the Wald statistic is  $\chi^2(6) = 9.43$ , with a p-value of .15. Symmetry and homogeneity are apparently rejected (and therefore not imposed) in the last block, with a Wald statistic of  $\chi^2(1) = 9.94$ , and an associated p-value of .001.

By and large, the estimates appear reasonable. The  $R^2$  statistics indicate that the equations fit well, and the Durbin-Watson statistics are close enough to 2.0 to indicate no obvious serial correlation in the residuals. Own-price coefficients are negative, and several cross-price coefficients are positive. The own-price coefficients are all statistically significant, and some of the cross-price terms are also significant, suggesting that it is useful to consider a vector of asset prices when attempting to model households' demands for money.

With respect to the error-correction parameters ( $\Gamma_{ij}$ ), we would typically expect own-stock adjustment coefficients to be negative, and cross-adjustment terms to be positive, although, as Barr and Cuthbertson (1990) point out, such restrictions are not required for dynamic stability. The own-error-correction parameters ( $\Gamma_{ii}$ ) do in fact turn out to be negative throughout the three blocks. In the liquid assets block some cross-correction terms ( $\Gamma_{ij}, i \neq j$ ) are positive, indicating that some of the components within the block are gross substitutes. A number of the cross-correction terms are statistically significant. For the case we are most interested in, money, the statistical significance of the cross-correction terms indicates that households adjust their money balances in response to prices of other assets with at least some lag.

We have included in the regressions one own-lag of the dependent variable, denoted  $\Delta s_{it-1}$ . At a practical level, the lagged dependent variable helps soak up autocorrelation and improves forecasts. At a theoretical level the inclusion of the lagged dependent variables can be justified by assuming that individuals face quadratic costs of adjusting their portfolios [see Cuthbertson (1985), p.64-67]. In the two-equation blocks, the adding-up constraint implies that the coefficients on the

$\Delta s_{it-1}$  must be of equal and opposite sign.

In the liquid asset block, we attempt to adjust for portfolio shifts owing to revaluations in long-term mutual funds by including as regressors the current-month change in the ten-year Treasury bond ( $\Delta Bond$ ) and the growth rate of the NYSE 5000 index ( $Gnyse$ ). In the mutual fund equation  $\Delta Bond$  has a negative sign, indicating that a drop in the yield of longer-dated Treasuries induces capital gains in mutual funds (or induces inflows into mutual funds). The same response is indicated by the positive sign on  $Gnyse$  in the mutual fund equation. Although the signs are reversed in the money equation, we cannot necessarily conclude that upturns in the market cause households to consciously shift balances to mutual funds. The money share could well fall with an upturn in the market because of capital gains accruing to mutual fund balances. Nevertheless, it seems reasonable to assume that some portion of share substitutability represents a conscious choice of households to shift balances between money and mutual funds.

Price elasticities for the AIDS model are in Table 4. The elasticities are measured at the means of the variables in the elasticity formulas in Table 1. In view of the coefficient estimates in Table 3, the elasticities offer few surprises. Own-price elasticities are negative and cross-price elasticities are typically positive. Notably, the cross-price elasticity between money and mutual funds is positive, indicating that retail investors view mutual funds as a substitute for money. Indeed, the elasticity of assets devoted to mutual funds with respect to an increase in the price of money is substantial (3.5), indicating that mutual funds are likely to be an important part of the explanation for the “missing M2”.

Table 4 : Elasticities<sup>1</sup>

		Price Elasticities			
		P1 $\eta_{1i}$	P2 $\eta_{2i}$	P3 $\eta_{3i}$	P4 $\eta_{4i}$
<u>Block</u>	<u>Equation</u>				
(1) Money	OCD,Sav,MMDA	-2.4	1.6		
	Small CD,MMMFs	1.3	-2.6		
(2) Liquid Assets	Money	-1.36	0.23	-.03	0.03
	Mutual Funds	3.47	-4.12	1.17	-.02
	Noncomp. Tenders	0.87	0.86	-1.96	0.05
	Savings Bonds	0.43	-.35	0.22	-1.82
(1) Liquid Wealth	Liquid Assets	-1.05	0.02		
	Consumer Liabs.	0.28	-1.08		

<sup>1</sup>Elasticities measured at means of independent variables

## 8. Does a Portfolio Approach Help Explain the “Missing M2”

The proof of the model, of course, is in the pudding. We therefore conducted simulations to determine whether a portfolio approach adds anything substantive to our understanding of money growth.

In the first experiment, we simulated shares of wealth using the estimates in Table 3. The simulations are in-sample, but are dynamic in the sense that the dependent variables are set to the first few actuals to obtain starting values but are simulated thereafter. The wealth share for money simulated in this fashion is plotted in Figure 3 against the actual money share. Although the share of wealth devoted to money dropped considerably from 1991 to 1993 the AIDS model has no tendency to overpredict the money share.

However, it may be more appropriate to consider asset flows. We do this by appending to the system (5) an equation that predicts nominal wealth  $W = w_t P_t$ .  $P_t$  is the level of the consumer price index, not the implicit price index  $P^*$  defined by equation 3. The equation that we use to predict nominal wealth is a simple error-correction formula relating nominal wealth to nominal disposable income and interest rate variables (t-statistics in parentheses):

$$\begin{aligned}
 \Delta W_t = & \quad .36 & \quad -.06 & (W_{t-1} - .92Y_{t-1}) & + .10 \Delta W_{t-1} & + .02 \Delta Y_t \\
 & (1.5) & (6.5) & (29.4) & (1.4) & (.57) \\
 +.01 \Delta Y_{t-1} & + .05R_{1t} & - .01R_{2t} & -.07 \Delta R_{1,t-1} & + .03 \Delta R_{2,t-1} & + .04 \text{Gnyse}_t \\
 & (.5) & (6.5) & (5.8) & (4.1) & (5.2) & (6.7)
 \end{aligned}$$

$$R^2 = .72 \quad DW = 2.0$$

where  $W_t$  is total liquid financial wealth of households,  $Y_t$  is personal income,  $R_{1t}$  is the opportunity cost of holding liquid financial assets, and  $R_{2t}$  is the opportunity cost of consumer credit, and  $Gnyse$  is the one month change in the NYSE 5000 index. Predicted values for  $W_t$  were then formed dynamically with simulations beginning in May 1984 or January 1988. Using these predicted values  $\hat{W}_t$ , predictions for asset levels can be formed as  $\hat{a}_t = \hat{W}_t \hat{s}_t$ . We form the predicted asset levels recursively, starting with block 3, proceeding to block 2, and finishing with block 1. That is, we first predict the total level of assets and liabilities before predicting the breakdown of assets in to money, mutual funds, noncompetitive tenders and savings bonds, and so forth. Predicted flows are given by  $\Delta \hat{a}_t$ . Predicted flows for money are plotted against actual flows in Figure 4. Although there is some tendency for the AIDS model to overpredict the growth of money, the tendency seems relatively innocuous, especially compared to Figure 1.

To test whether the AIDS model helps to explain some of the missing M2, we computed forecast-encompassing statistics (Chong and Hendry, 1986) using the regression:

$$error_t^M = \theta(\hat{f}_t^M - \hat{f}_t^A) \quad (6)$$

In this regression,  $error_t^M$  is a forecast error from a standard money demand model,  $\hat{f}_t^M$  is the associated forecast from the standard money demand model, and  $\hat{f}_t^A$  is the AIDS model forecast. If the AIDS model adds anything to our understanding of money, then differences in the forecasts should help to explain the forecast error from standard money demand models. We can also estimate (6) replacing  $error_t^M$ , the forecast error from the money demand model, with the forecast error obtained from our AIDS model,  $error_t^A$ . The AIDS model is said to forecast-encompass the money demand model if  $\theta$  is significant in the regression using  $error_t^M$ , but insignificant in the regression using  $error_t^A$ . Strictly speaking, the forecast-encompassing statistics should use out-of-sample forecasts, rather than in-sample forecasts. However, by using in-sample forecasts the forecast-encompassing statistics can also be viewed as Davidson-MacKinnon D-statistics. A significant D-statistic (significant t-statistic on  $\theta$ ) indicates that the model is misspecified. We estimate these regressions with errors and forecasts measured as growth rates.

The variable  $error_t^M$  is generated in two ways. The first way takes the forecast error from the Federal Reserve Board's monthly model of the demand for M2 balances. The model is estimated over the period January 1964 to July 1993, and forecasts are obtained by dynamic simulations starting in May 1984 or January 1988 and running to July 1993. However, because we have excluded



currency and demand deposits from our analysis, while the Board’s model—being a model of M2 demand—includes them, our second means of generating  $error_t^M$  uses precisely the data used by our AIDS model to estimate a “standard money demand model”. It is a two-step error-correction model similar in spirit to the Federal Reserve Board’s money demand model (Moore, Porter, and Small, 1990):

$$m_t = -.85 + 1.0y_t + .30Opcost_t + \epsilon_t, \quad R^2 = .99, \quad DW = .07$$

$$\begin{aligned} \Delta m = & \quad .006 & - .011 \hat{\epsilon}_{t-1} & + .54 \Delta m_{t-1} & + .028 \Delta Opcost_{t-1} \\ & (6.2) & (1.93) & (9.3) & (5.2) \\ & - .037 \Delta cons_t & + .061 \Delta cons_{t-1} & - .036 \Delta cons_{t-2} & + .04E-4 t \\ & (1.0) & (1.9) & (1.2) & (4.9) \\ & + .003 Dum1 & + .007 Dum2 & - .002 Dum3 & + .002 DumMMDA \\ & (2.0) & (3.4) & (1.5) & (2.6) \end{aligned}$$

$$R^2 = .75 \quad DW = 1.84$$

where  $m_t$  is the log of money defined as the sum of OCDs, savings, MMDAs, retail money funds, and small CDs. The variable  $y_t$  is the log of nominal personal income,  $Opcost$  is the opportunity cost of holding  $m_t$ , and  $cons_t$  is the log of nominal consumption. The variables Dum1, Dum2, Dum3, and DumMMDA are the dummy variables:

<u>Dum1:</u>	dummy for credit controls: 1 in Apr, May and June 1980, 0 otherwise
<u>Dum2:</u>	dummy for nationwide introduction of NOW accounts; 1 in Jan, Feb, Mar 1983, 0 otherwise
<u>Dum3:</u>	same as Dum2, but 1 in Apr, May, Jun 1983, 0 otherwise
<u>DumMMDA:</u>	dummy for the introduction of MMDAs: 0 through Dec 1982, 1 thereafter

The model, estimated over January 1976 to July 1993, fits well and the coefficient estimates are similar to those reported in Moore, Porter, and Small (1990). As before, we obtain the forecast errors  $error_t^M$  with dynamic simulations beginning in May 1984 or January 1988 and running to July 1993.

Table 5 presents results of the forecast-encompassing regressions (6). The results are generally favorable to the AIDS model. It helps predict the forecast errors (that is  $\theta$  is statistically significant) from both the “standard” money demand model and the Federal Reserve Board’s (FRB) money model, and, in terms of  $R^2$ , it explains a large proportion of the variance in their forecast errors. For example, in the simulation using the Board’s model over the period January 1988 to July 1993—the comparison least favorable to the AIDS model—the AIDS model explains 48% of the forecast errors

in the FRB model. Conversely, the FRB model explains only 29% of the forecast error from the AIDS model. The results are considerably more favorable to the AIDS model when the simulations come from the “standard model”. The potential gains in forecast accuracy reported in Table 5 are comparable with the gains that Duca (1993, 1994) reports from estimating standard models that rely on an augmented monetary aggregate consisting of M2 plus the assets of long-term mutual funds.

Table 5 : Does the AIDS Model Help Predict Money Growth?  
Forecast-encompassing tests based on regression:  $error_t = \theta(\hat{f}_t^M - \hat{f}_t^A)$

“Standard” money demand model					FRB’s Money Demand Model				
Simulation Date Range					Simulation Date Range				
84:5 to 93:6					84:5 to 93:6				
$error_t$ from	t-stat	$R^2$	t-stat	$R^2$	$error_t$ from	t-stat	$R^2$	t-stat	$R^2$
AIDS model	3.3	.10	1.6	.04	AIDS model	5.2	.19	5.1	.29
Money model	7.1	.31	7.3	.44	Money model	9.3	.43	8.4	.48

## 9. Conclusion

An essential assumption of much recent research on the monetary transmission mechanism is that households adjust their balance sheets slowly in response to changes in opportunity costs. The slower than anticipated growth of M2 since 1990 is a related, troublesome question. Evidence on both phenomenon are provided by the model in this paper. Our estimates suggest that bond and equity mutual funds display a sizable cross-elasticity of substitution with respect to the monetary assets included in M2. This may not be surprising, since mutual funds display some properties usually associated with money, including high liquidity and some check writing privileges. Of more importance, perhaps, is that the assets of long-term mutual funds are precisely the “other” types of capital market instruments that feature prominently in transmission mechanism models. Our estimates suggest that the participation of households may be less limited than has been assumed.

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